INTELLIGENT DETECTION OF ABNORMAL NEONATAL CEREBRAL HAEMODYNAMICS IN A NEONATAL INTENSIVE CARE ENVIRONMENT

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***Abstract* - In this paper, we investigate an advanced monitoring system for a neonatal intensive care unit. The system intelligently detects abnormal neonatal cerebral Doppler ultrasound signals by means of principal component analysis and a non-normalised compensatory neuro-fuzzy rule based algorithm. Two hundred and ninety Doppler ultrasound signals were recorded from the anterior cerebral arteries of 40 normal full-term babies and 14 mature babies with intracranial pathology. The features of the normal and abnormal groups were extracted from the maximum velocity waveforms using a principal component method. The non-normalised compensatory neuro-fuzzy rule based algorithm yielded the highest predictive accuracy of 76.21%. These results show that the proposed algorithm is superior to others, and could potentially be used to build an intensive neonatal care unit system for the intelligent detection of abnormal neonatal cerebral haemodynamics.**

Keywords - Neonatal cerebral arteries, Doppler ultrasound, blood flow velocity, principal component analysis, decision-making systems, compensatory fuzzy neural networks, pattern classification.

I. INTRODUCTION

Designing intelligent diagnostic systems has been an important component of research efforts in biomedical and clinical engineering for the last three decades [1]. These systems have been designed to aid medical staff (doctors and nurses), to increase their ability and reliability during decision making in diagnosis. However, for intensive care units (ICUs), not much research has been conducted. Among specialist ICUs, a neonatal intensive care unit is one of the busiest departments that requires more careful consideration. Recent studies dealing with the use of intelligent systems in ICUs are very encouraging and show that such systems have become a necessity, with staff demonstrating willingness and interest in their use [2].

Abnormal cerebral haemodynamics is a condition that causes brain death and severe disability. Doppler ultrasound has been used to detect abnormal cerebral haemodynamics in both full-term and pre-term infants with a variety of pathological conditions [3,4] since this is a non-invasive and objective diagnostic method [5].

Changes in the Doppler frequency envelope signal have been quantified by measuring changes in Pourcelot's resistance index (PI) [6]. This index is defined as (S-D)/S, where S and D are the maximum and minimum values of the Doppler shift frequency envelope during each cardiac cycle. PI is very simple to calculate, but is not suitable for detecting abnormalities if there are not gross changes in the Doppler waveform shape.

Principal component analysis (PCA) has been shown to be a very efficient feature extraction technique for detecting changes in Doppler waveforms compared with PI [3,5,7,8].

Individual use of PI and PCA has been demonstrated to be ineffective for the reliable diagnosis and interpretation of abnormal cerebral haemodynamics [3,5,7]. It has therefore become necessary to find more accurate models for detecting abnormal changes rather than using PI and PCA individually.

Pattern recognition methods such as Generalised Linear Function (GLF), Bayes' Model and Artificial Neural Networks (ANNs) have been investigated to detect such changes [7-10].

Seker and Evans have recently proposed a compensatory neuro-fuzzy rule based algorithm for the detection of abnormal changes in neonatal cerebral arteries, and showed it to be superior to the previously applied methods such as ANN, GLF and Bayes' method [11].

It has also been demonstrated that a fuzzy system without normalisation converges much faster than a fuzzy system with normalisation [12]. Seker et al. examined this idea to further improve the capability of the compensatory fuzzy algorithm for function approximation in general [13]. They showed that the non-normalised version of the algorithm yielded not only lower errors, but also used less memory and CPU time.

In this paper, we examine a non-normalised compensatory neuro-fuzzy rule based algorithm to detect abnormal changes in velocity waveforms from the anterior cerebral arteries of newborn babies, and its possible use in a neonatal intensive care unit.

II. NEONATAL CEREBRAL HAEMODYNAMICS DETECTION SYSTEM

The block diagram in Fig. 1 illustrates the system for detecting neonatal cerebral haemodynamics.

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A Doppler unit is used to measure blood velocity changes based on the concept of the Doppler shift signal, and a signal-processing unit is used to analyse the measured signals. In this part of the system, Fast Fourier Transformation (FFT) is used to extract Doppler ultrasound sonograms. In the feature extraction unit, the maximum frequency envelope is extracted from each sonogram, and an ensemble average waveform derived. The ensemble average waveforms are then subjected to principal component analysis (PCA) to reduce their dimensionality, so that each waveform can be represented by a pair of coordinates which can then be used in the classification of each waveform as either normal or abnormal. Further details of this process can be found in [3,5]. Subsequently, the coefficients are sent to the decision making part of the system, where the proposed compensatory neuro-fuzzy model, the parameters of which have previously been tuned, will decide on whether the waveform is normal or otherwise.

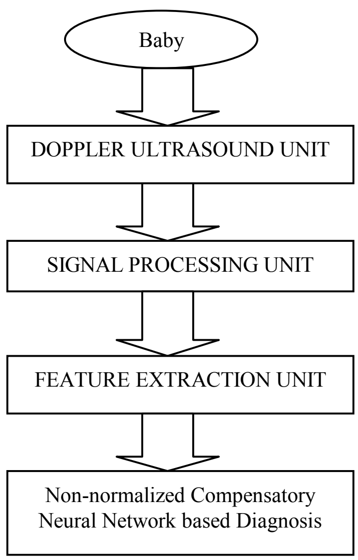

Fig.1. Block diagram of the system

III. A COMPENSATORY NEURO-FUZZY SYSTEM

A fuzzy logic system is a model with linguistic IF-THEN rules [14]. Such a fuzzy logic system of r-rules and an n-input-one-output can be defined as

IF x_1 is M_{1r} and ... x_i is M_{ir} and ... x_n is M_{nr} **THEN** y is O^r

where M_{ir} and O^r are input and output fuzzy sets of a rule r (r=1,2,...R), respectively; $x=(x_1,...,x_i,...,x_n)$ is an n-dimensional input vector; and y is the output of the system.

Since the final output of a fuzzy system is a function of all rules, a compensatory neuro-fuzzy system (CNFS) can be defined as:

$$o(x)=\frac{\sum_{r=1}^{R} V_{out}(r).\sigma_{out}(r).\left[\prod_{i=1}^{n}\mu_{M_{ir}}(x_i)\right]^{1-c^r+c^r/n}}{\sum_{r=1}^{R} \sigma_{out}(r).\left[\prod_{i=1}^{n}\mu_{M_{ir}}(x_i)\right]^{1-c^r+c^r/n}}$$

where $\mu_{Mir(x_i)}$ is a membership function of M_{ir} input fuzzy sets of rule-r and input variable x_i, $V_{out}(r)$ and $\sigma_{out}(r)$ are centre and width parameters of O^r output fuzzy sets of rule-r, respectively, and c^r is the compensatory parameter of rule-r [14].

The non-normalised CNFS may be defined as:

$$o(x)=\sum_{r=1}^{R} V_{out}(r).\sigma_{out}(r).\left[\prod_{i=1}^{n}\mu_{M_{ir}}(x_i)\right]^{1-c^r+c^r/n}$$

The parameters of both the input (M_{ir}) and output (O^r) fuzzy sets of the CNFS are adjusted using the back propagation technique [15] to design an optimal CNFS. We refer readers to [11,13] for further information about the adjustment of the parameters.

If appropriate initial parameters are chosen, the back propagation algorithm converges faster. Therefore, in this paper, we use the fuzzy c-means (FCM) clustering method [16,17], which is a well-known and widely used technique, to initialise the CNFS model. We refer readers to [11,13] for further information about the initialisation.

IV. METHODS

Fifty-four newborn babies were studied. Among them, there were 40 normal full-term babies and 14 mature babies with intracranial pathology. Doppler signals were recorded from both anterior cerebral arteries of each baby on one or more occasions, and 290 test signals were recorded. Values of the maximum frequency envelope of the Doppler signal at 12.5 msec intervals for each signal were extracted. Fig.2 shows examples of sonograms of Doppler signals recorded from a healthy baby and from one with severe birth asphyxia. In this case, the waveform from the ill baby, regarded as an abnormal waveform, is very much less pulsatile than that from the normal baby. However, it is not always an easy task to distinguish a normal waveform from an abnormal one as suggested by Fig. 2.

Principal component analysis was carried out on an ensemble average of each series of beats. The first 350 msec of each waveform were taken and normalised to its mean height. Then, the first two coefficients of the principal components were derived from the 290 test waveforms, which were used as a feature set for all the algorithms studied.

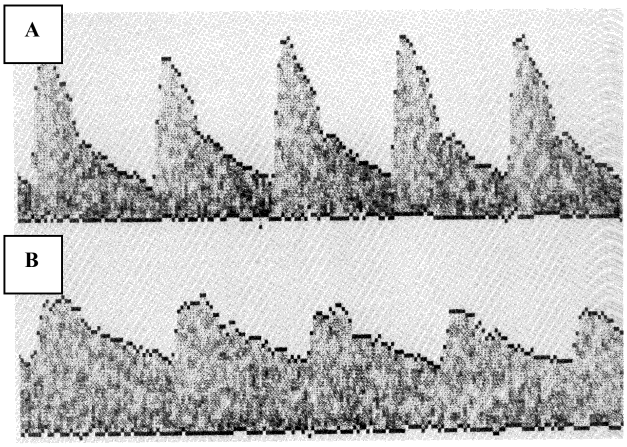

Fig. 2. Sonogram of the Doppler signals recorded from (A) a normal baby and (B) a baby with severe birth asphyxia.

V. RESULTS

As reported in [11], the normalised version of a compensatory neuro-fuzzy rule based algorithm significantly outperformed ANN, Bayes' Model and GLF. In this study, there was a 5-rule fuzzy system which had 35 updated parameters.

Normalised and non-normalised CNFS with 7 fuzzy rules and initial compensatory degree of 0.25 were trained for 1000 iterations. The data set was divided into a training and test sets, each comprising of 145 exemplars. The results are listed in Table 1. These results show that the proposed algorithm yielded a higher predictive accuracy. Moreover, the experiment showed that the non-normalised version of the CNFS used less memory and CPU time as reported in [13].

VI. CONCLUSIONS

We have shown that, for the detection of abnormal neonatal cerebral Doppler ultrasound waveforms modelled by PCA, the non-normalised CNFS is a very efficient hybrid method. It incorporates the techniques of fuzzy logic, back propagation learning and FCM and, compared with previously used methods, it yields not only higher predictive accuracy but also higher speed and lower memory usage. It can be concluded that this model could be used to build a future intelligent system in a neonatal intensive care unit to serve all medical personnel in the unit by increasing their flexibility and enhancing their ability to make reliable diagnostic decisions.

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TABLE I
COMPARISON OF THE ALGORITHMS IN TERMS OF PREDICTIVE ACCURACY (%)

	Training Data Set	Test Data Set	Total
Normalised CNFS	68.97	65.86	67.41
Non-normalised CNFS	78.97	73.47	76.21

REFERENCES

[1] D.L. Hudson and M.E. Cohen, *Neural Networks and Artificial Intelligence for Biomedical Engineering*, IEEE Press, NY, USA, 2000.

[2] M. Frize and R. Walker, "Clinical Decision-Support Systems for Intensive Care Units Using Case Based Reasoning", Medical Engineering & Physics, vol. 22, no.9, Nov. 2000, pp:671-677.

[3] D.H. Evans, L.N.J. Archer and M.I. Levene, "The detection of abnormal neonatal cerebral haemodynamics using principal component analysis of the Doppler ultrasound waveform", Ultrasound Med. Biol., vol. 11, 1985, pp:441-449.

[4] J.B. McMenamin and J.J. Volpe, "Doppler ultrasonography in the determination of neonatal brain death", Ann. Neurol., vol.14, 1983, pp:302-307.

[5] D.H. Evans, "The Interpretation of Continuos Wave Ultrasonic Doppler Blood Velocity Signals viewed as a problem in pattern recognition", Journal of Biomed Eng., vol.6, Oct. 1984, pp:272-280.

[6] L. Pourcelot, "Diagnostic Ultrasound for Cerebral Vascular Diseases", In *Present and Future of Diagnostic Ultrasound*, (edited by Donald I and Levi S), Kooyker Scientific Publ., 1976; 141-7.

[7] D.H. Evans and A. Caprihan, "The application of classification techniques to biomedical data with particular reference to ultrasonic Doppler blood velocity waveforms", IEEE Trans. BME, vol. 32, 1985, pp:301-11

[8] D.H. Evans, D.S. Macpherson, S. Bentley, M.J. Asher and P.R.F. Bell, "The effect of proximal stenosis on Doppler waveforms: a comparison of three methods of analysis in an animal model", Clin. Phys. Physiol. Meas., vol.2, 1981, pp:17-25.

[9] Z. Guo, L.G. Durand, L. Allard, G. Cloutier, H.C. Lee, "Classification of lower limb arterial stenoses from Doppler blood signal analysis with time-frequency representation and pattern recognition techniques", Ultrasound Med. Biol., vol. 20, 1994; pp:335-46.

[10] I.A.Wright, N.A.J. Gough, F. Rakebrandt, M. Wahab and J.P. Woodcock, "Neural network analysis of Doppler ultrasound blood flow signals : a pilot study", Ultrasound Med. Biol., vol. 23, 1997, pp:683-90.

[11] H. Seker and D.H. Evans, "Intelligent Detection of Abnormal Neonatal Cerebral Doppler Ultrasound Waveforms using Compensatory Hybrid Fuzzy Neural Networks", Proceedings of the 3rd International Workshop on Biosignal Interpretation, June 12-14 1999, Chicago, USA, pp:284-287.

[12] Y. Lin and G.A. Cunningham, "A new approach to fuzzy-neural system modelling", IEEE Trans. Fuzzy Systems, vol.3, 1995, pp:190-197.

[13] H. Seker and D.H. Evans, "Non-normalized compensatory hybrid fuzzy neural networks", Proceedings of the International Joint Conference on Neural Networks, July 10-16 1999, Washington, DC, USA, IEEE Press, v.6, (1999), pp:4300-4303.

[14] Y.Q. Zhang and A. Kandel, "Compensatory neurofuzzy systems with fast learning algorithms", IEEE Trans. Neural Networks, vol.9, 1998, pp:83-105.

[15] S. Haykin, *Neural Networks : A Comprehensive Foundation*, New York, Macmillian, 1994.

[16] J. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*, New York: Plenum Press, 1981.

[17] H. Seker, *Classification of Electromyographic Signals By Using Fuzzy Classifiers*, M.Sc. Thesis, Istanbul Technical University, Istanbul, Turkey,1995.